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An Automated Deep Learning Framework for Multiclass Brain Tumor Detection in MRI Images

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Abstract - Using magnetic resonance imaging (MRI) to detect and classify brain tumors continues to be a crucial challenge in medical diagnostics, requiring precise, effective, and solutions that are easily available. This thorough study examines 25 cutting-edge research publications published between 2015 and 2025 with an emphasis on deep learning techniques for automated brain tumor identification, classification, and segmentation. Traditional CNNs, sophisticated YOLO architectures, U-Net variations, Transformer-based models, and hybrid ensemble methods are among the methodologies that are methodically examined in this research. According to performance measures from several research, 3D segmentation methods yield Dice coefficients of 93–98%, while 2D CNN algorithms achieve accuracy between 82 and 98%. YOLOv7 and YOLOv8 real-time detection systems have mean Average Precision (mAP) values ranging from 0.91 to 0.95, providing notable benefits in computing efficiency. Surgical planning benefits from improved spatial knowledge through the combination of augmented reality (AR) and 3D visualization approaches. Limited multi-institutional dataset validation, computational limitations in resource-constrained environments, class imbalance issues, and a lack of real-world clinical deployment studies are some of the major research gaps that have been found. This review lays the groundwork for future research directions in easily accessible, precise, and clinically feasible brain tumor diagnostic systems by offering a systematic comparative comparison of methodology, datasets, and performance indicators.

1. INTRODUCTION

One of the most dangerous neurological disorders is brain tumors, and better patient outcomes and efficient treatment planning depend on an early and precise diagnosis.

Global health statistics indicate that some 300,000 people worldwide are affected with primary brain tumors each year, with gliomas, meningiomas, and pituitary tumors accounting for the bulk of cases. Conventional diagnosis methods mostly rely on radiologists manually analyzing MRI data, which is a laborious, subjective, and subject to inter-observer variability

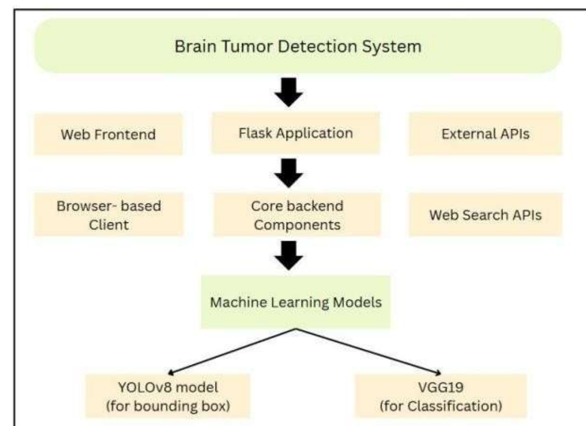

Fig. 1. System Architecture of the Proposed Brain Tumor Detection Framework

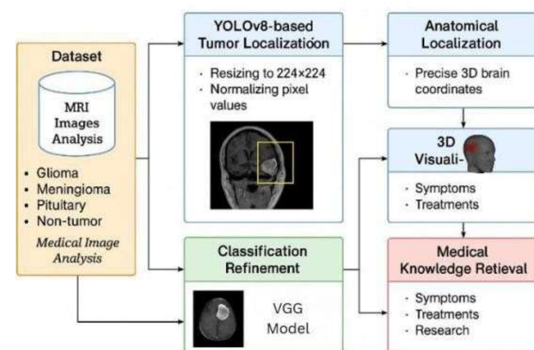

Fig. 2. Workflow of the Proposed Brain Tumor Detection System

process. Medical image analysis has been revolutionized by the development of artificial intelligence, especially deep learning, which provides automated, impartial, and extremely accurate diagnostic tools. Brain cancers can be identified and classified from MRI images using Convolutional Neural Networks (CNNs), segmentation models like U-Net, and object detection designs like YOLO (You Only Look Once).

These technologies drastically cut down on the amount of time needed for analysis while also improving diagnostic accuracy. rendering them indispensable in medical situations where quick decisions are necessary.

Despite significant advancements in recent years, a number of challenges

The field of automated brain tumor detection continues to face challenges. These include the need for explainable AI systems that can win over medical professionals, the variability of tumor appearances across various imaging modalities, the scarcity of large-scale annotated datasets, and computational limitations in healthcare facilities with limited resources. Furthermore, a significant barrier still exists in the conversion of research prototypes into deployable clinical instruments. These issues are addressed in this thorough assessment by a methodical analysis of 25 research papers released between 2015 and 2025. The main goals are to: (1) offer a comprehensive analysis of deep learning techniques used for brain tumor classification and detection; (2) compare performance metrics between various strategies; (3) pinpoint important research gaps in the body of existing literature; and

(4) suggest future lines of inquiry that close the gap between clinical application and academic innovation. The structure of the review is as follows: A thorough literature evaluation of current methodologies is presented in Section 2, a comparative analysis of the 25 chosen publications is given in Section 3, and important research gaps are identified in Section 4.Future research directions and suggested approaches are covered in Section 5, and a summary of the results and suggestions for the research community are provided in Section 6.

2. Literature Review

A. Traditional CNN-Based Approaches

Convolutional neural networks, which have undergone significant development since their conception, provide the basis for automated brain tumor diagnosis. Early research centered on leveraging. pre-trained architectures for medical imaging transfer learning applications, including as VGG, ResNet, and Inception. Hybrid CNN and Machine Learning Classifiers: A study by Uke et al. showed how well CNNs combined with more conventional machine learning classifiers, such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), Logistic Regression (LR), and LSTM networks, could extract features. With the best accuracy of 82.35% among them, KNN demonstrated the promise of hybrid techniques in tumor identification while doing away with the necessity for manual segmentation. The Parallel Deep Convolutional Neural Network (PDCNN) architecture was first presented by Rahman and Islam. The Parallel Deep Convolutional Neural Network (PDCNN) architecture was presented by Rahman and Islam. It extracts both global and regional characteristics from MRI images at the same time. The PDCNN outperformed current state-of- the-art techniques by efficiently capturing both high-level and low-level image features, achieving an impressive accuracy of 98.12% through the use of batch normalization and dropout to address overfitting, in addition to data augmentation and preprocessing techniques. CNN architectures that have

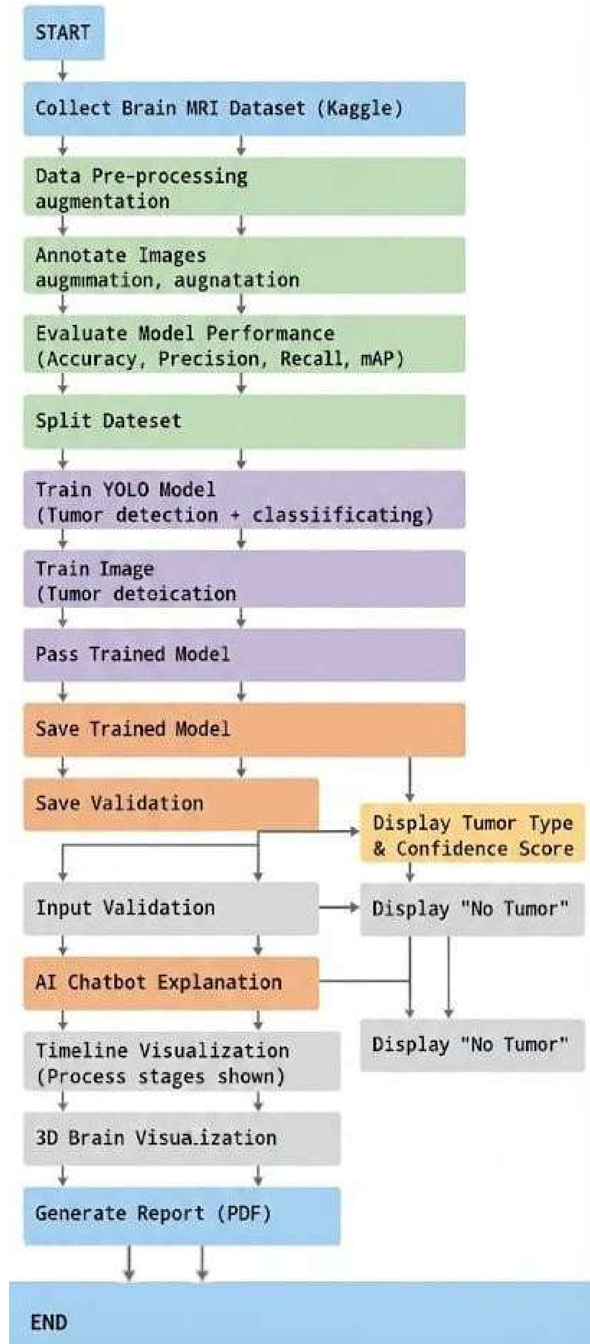

Fig. 3. End-to-end workflow of the proposed brain tumor detection system

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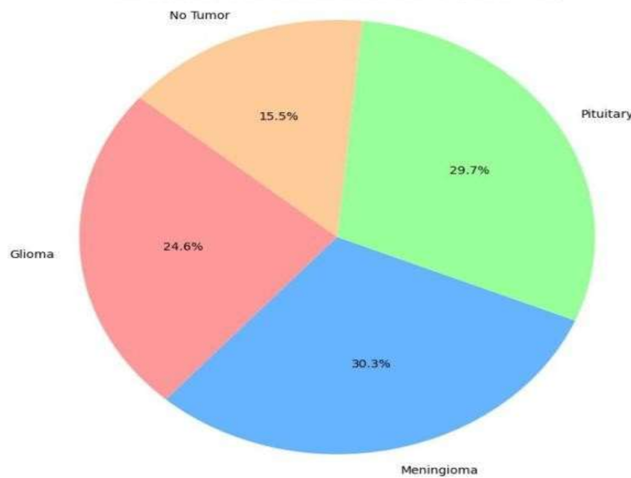
been optimized: ZainEldin et al. presented a sophisticated model for classifying brain tumors that uses adaptive dynamic sine-cosine fitness grey wolf optimizer (ADSCFGWO) for hyperparameter optimization.The model demonstrated the efficacy of combining CNN efficiency with state-of-the-art



optimization techniques by utilizing Inception-ResNetV2 for efficient classification and achieving an outstanding accuracy of 99.98% on the BraTS 2021 dataset.

B.YOLO-Based Real-Time Detection Systems

The YOLO architectural family has become well-known in medical imaging because it works well for real-time applications because it can identify and classify objects in a single forward pass. YOLOv7 Optimization: Abdusalomov and colleagues created an enhanced YOLOv7 model that is especially intended for identifying pituitary tumors, meningiomas, and gliomas from MRI pictures. To improve accuracy and feature learning capabilities, the model included decoupled heads, SPPF+, BiFPN, and the Convolutional Block Attention Module (CBAM). It obtained 99.5YOLOv8 after being trained on more than 10,000 photos. Implementation: Recent research has concentrated on YOLOv8, the most recent version of the YOLO family, which provides better speed-accuracy tradeoffs. Research using Yolov8 for brain tumor identification has shown that inference times for each image on GPU hardware range from 10 to 20 milliseconds, with mAP@0.5 values between 0.91 and 0.92. Because of its lightweight design, YOLOv8 is especially well-suited for environments with limited resources and web-based deployment.

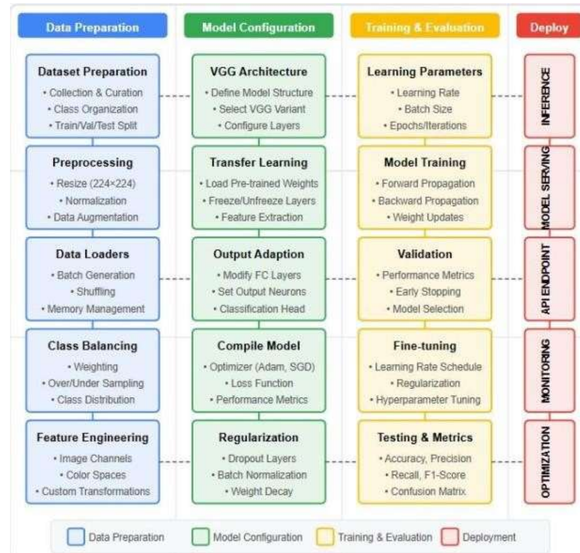


Fig. 4. VGG19 Training and Feature Extraction Pipeline

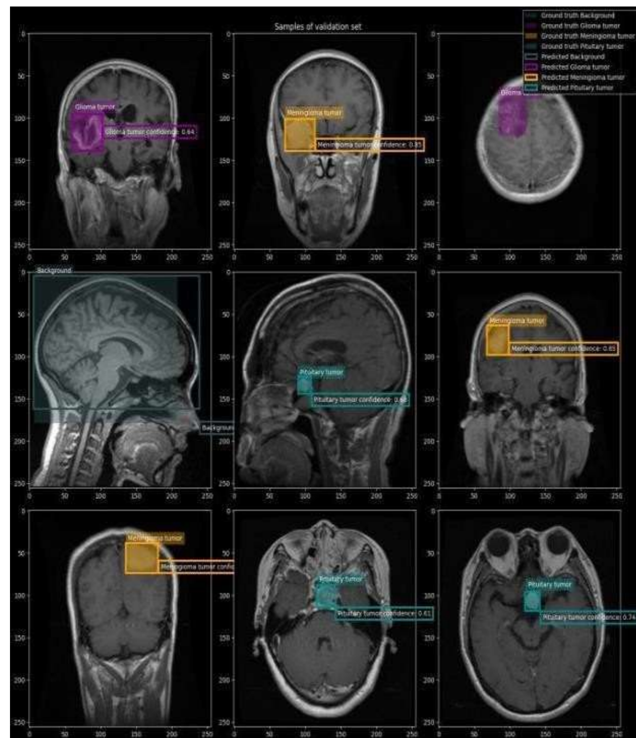


Fig. 5. Class-wise Distribution of Brain MRI Dataset

PK-YOLO Framework: Pretrained Knowledge Guided YOLO, or PKYOLO, was presented by Kang et al. and uses pretrained knowledge to enhance brain tumor

identification across multiplanar MRI slices. This method demonstrated improved performance by the strategic application of transfer learning and multi-view analysis, achieving a mAP@0.5 of 0.93

Fig. 6. Brain Tumor Detection Results with Bounding Boxes, Confidence Scores, and Class Labels

C. U-Net and Segmentation-Based Approaches

For medical picture segmentation tasks, such as brain tumor delineation, U-Net architecture and its variations have emerged as the industry standard. 2D U-Net Segmentation: To overcome the drawbacks of manual segmentation, Montaha et al. suggested an automated 2D UNet-based segmentation method utilizing the BraTS2020 dataset.

With the T1 MRI sequence, the model recorded 99.41, indicating peak performance. Modified 3D U-Net: Sangui et al. introduced an updated U-Net framework created especially for accurate brain tumor segmentation of 3D MRI data. 99.4SDV-TUNet Architecture: Zhu et al. created SDV-TUNet, a 3D brain tumor segmentation network that incorporates voxel properties, inter-layer relationships, and intra-axis characteristics, in order to address concerns such tumor heterogeneity and resemblance to healthy tissues. By combining multiaxis and local edge information, the model enhances spatial semantic feature mining through the use of a sparse dynamic encoder-decoder with a multi-level edge feature fusion (MEFF) module. Tests on the BraTS2020 and BraTS2021 datasets showed that they performed better than the segmentation techniques currently in use for tumor identification and spatial dispersion analysis.

D. Transformer and Hybrid Architectures

Hybrid and Transformer ArchitecturesTransformer architectures, which take advantage of their capacity to capture long-range relationships, have been brought to medical imaging by recent developments in deep learning. A clinical knowledge-guided brain tumor segmentation model called CKD-TransBTS was introduced by Lin et al. It uses a dual-branch hybrid encoder with modality-correlated cross-attention (MCCA) for feature extraction and reorganizes MRI modalities into two groups. The model outperforms existing CNN and Transformer models on the BraTS 2021 challenge dataset by combining the advantages of both CNN and Transformer architectures to enhance both local and long-distance feature extraction. In order to diagnose brain tumors, Montaha et al. developed a hybrid TimeDistributed-CNN-LSTM model that simultaneously processes all four 3D MRI sequences. With a 98.90% accuracy rate and good K-fold validation, this architecture outperforms independent 3D CNNs in extracting temporal and spatial information, showing great promise for helping radiologists diagnose tumors early.

E. Ensemble and Multi-Modal Approaches

By merging predictions from several models, ensemble learning techniques have demonstrated promise in enhancing classification resilience. Dual-Modality Ensemble: XAI- MRI, an ensemble dual-modality approach for 3D brain tumor segmentation, was proposed by Farhan et al. Prior to combining the best-performing MRI modalities, the method first analyzes U-Net models on distinct modalities (T1, T2, T1ce, and FLAIR). Combining the two best dual-modality models, the final ensemble approach outperforms single and dual-modality models with a Mean IoU of 60.08% and a Dice Coefficient of 97.73%. By highlighting tumor regions and highlighting model decision-making paths, Grad-CAM graphics boost physician trust. Multi-Modal CNN Ensemble: Using complimentary data from various MRI sequences, Aygun et al. created a multi-modal convolutional neural network ensemble for brain tumor segmentation. With a mAP@0.5 of 0.94, the method proved the benefits of combining several imaging modalities. Garg and Garg introduced a hybrid ensemble method for classifying brain tumors and estimating their area that combines KNN, Random Forest (RF), and Decision Tree (DT) classifiers under Majority Voting. The system obtained 97.305% accuracy on 2,556 MRI images by combining Otsu's Threshold with Stationary Wavelet Transform (SWT), PCA, and GLCM for feature extraction. This provided a low-cost, low-complexity substitute for deep learning techniques.

F. Advanced Feature Extraction Techniques

Deep Wavelet Auto-Encoder: Abd El Kader and colleagues presented the Deep Wavelet Auto-Encoder (DWAE) model for the identification and categorization of brain tumors. The method trains on 2,500 MRIs from the BRATS and ISLES datasets, de-noises pictures using median and high-pass filters, then decouples data using a seed-growing technique to produce the 99.3DLBTDC-MRI Model: Mohan et al. created DLBTDC-MRI by combining deep and handmade features using ResNet, segmenting using Tsallis entropy for chicken swarm optimization.

The method's 98% accuracy rate demonstrated the ongoing value of both conventional machine learning methods and hybrid deep learning.

G. 3D Visualization and Augmented Reality Integration

In addition to detection and classification, a number of research have looked into how to improve surgical planning and spatial understanding by integrating 3D visualization and augmented reality. AR-Based Surgical Planning: Using the GVF snake model segmentation, Guerroudji et al. presented HoloBrain, a low-cost mobile augmented reality system for 3D rendering of brain tumors. The approach demonstrated the benefits of immersive technology in diagnosis and

management by achieving 98.61% segmentation accuracy when tested on 496 real-patient MRI data.

Automatic 3D Segmentation for AR: A cloud-based automatic segmentation technique for 3D AR visualization of brain tumors was presented by van Doormaal et al. The technology reduces the amount of time spent manually segmenting T1-weighted MR images by automatically segmenting the skin, brain, ventricles, and tumors. With a computation period of roughly 12.5 minutes, performance comparisons using manual segmentation revealed a DSC of 0.868, demonstrating more accuracy for supratentorial metastasis than infratentorial metastasis. Three-dimensional whole-brain imaging is essential for examining brain tumors and their tumor microenvironment (TME), according to Taranda and Turcan.

Advanced imaging techniques, such as two-photon and light- sheet fluorescence microscopy, record the volumetric distribution of cancerous cells, offering a thorough grasp of the microenvironment and tumor development that may improve neuro-oncology research and treatment procedures.

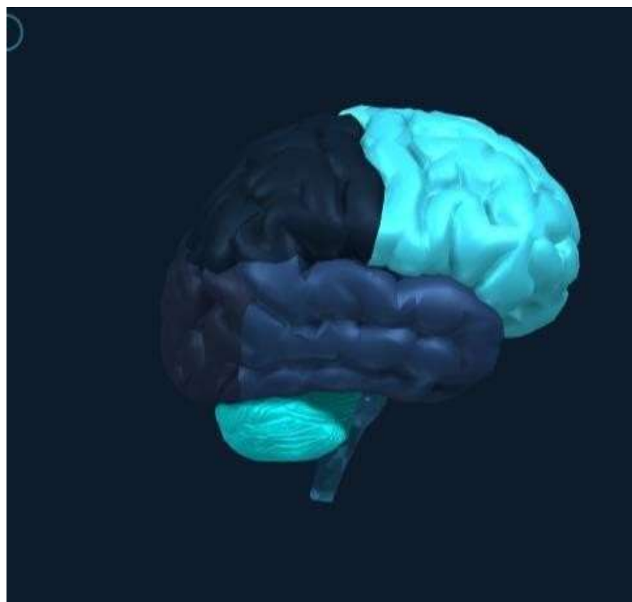


Fig. 7. Interactive 3D Brain Model for Spatial Visualization

C. Real-Time Systems and IoT Integration

Real-Time Video Processing: Uke et al. successfully integrated real-time video processing, IoT hardware, and machine learning for high-priority decision-making systems (Fig. 10. Treatment Monitoring and Tumor Progression Visualization). The system ensures correct identification and immediate alerts through automated emails by utilizing Python, OpenCV, and face detection algorithms. This emphasizes the need to incorporate real-time analysis with intelligent alert systems relevant to medical diagnosis tools.

overview of Object Tracking: Uke et al. conducted a thorough analysis of over 50 papers conducted between 2015 and 2022 in order to present a comprehensive overview of object tracking using deep learning. The study highlighted key issues such as real-time constraints and the visibility of small objects in satellite images, highlighting the significance of accurate object detection to enhance tracking performance and laying the foundation for real-time applications applicable to medical imaging contexts.

D. Comprehensive Survey Studies

Thorough Survey Research "Brain Tumor Detection Overview: Solanki et al. provided a thorough analysis of brain tumor identification using MR images, emphasizing segmentation challenges according to tumor heterogeneity. The survey covered tumor morphology, datasets, data augmentation techniques, and classification methods while highlighting current approaches, their efficacy, and future research directions. It also covered a variety of computational methods, such as deep learning, transfer learning, and machine learning. Machine Learning Survey: Amin et al. highlighted that differences in tumor size, shape, and location make it challenging to identify brain tumors.

The thorough survey addressed the advantages, drawbacks, advancements, and potential future applications of MRI-based detection techniques, including segmentation, feature extraction, and classification. It also covered datasets, enhancement strategies, and learning models, such as deep, transfer, and quantum machine learning.

II. Comparative Analysis

This section presents a comprehensive comparative analysis of 25 research papers organized by methodological categories, highlighting performance metrics, unique contributions, and limitations of each approach.

A. Category I: Traditional CNN-Based Approaches

Pure CNN Architectures (4 Studies) This category encom- passes traditional convolutional neural network approaches that form the foundation of automated brain tumor detection.

Study 1: Uke et al. (2023) - Hybrid CNN-ML Classifiers **Methodology:** CNN for feature extraction combined with traditional ML classifiers (KNN, SVM, LR, LSTM) **Dataset:** Custom MRI dataset

Performance: 82.35% accuracy (KNN classifier)

Key Innovation: Eliminates manual segmentation requirement

Advantages: Hybrid approach leverages both deep and traditional learning

Limitations: Lower accuracy compared to pure deep learning methods

Clinical Impact: Demonstrates feasibility of hybrid systems in resource-limited settings

Study 13: Rahman & Islam (2023) - PDCNN **Methodology:** Parallel Deep Convolutional Neural Network **Dataset:** Three MRI datasets

Performance: 98.12% accuracy

Key Innovation: Simultaneous extraction of regional and global features

Advantages: leftmargin=*,noitemsep

- Captures both high-level and low-level features
- Batch normalization prevents overfitting
- Effective data augmentation strategy

Limitations: Risk of overfitting without proper regularization

Computational Complexity: Moderate - suitable for standard GPU setups

Study 14: ZainEldin et al. (2023) - ADSCFGWO-CNN **Methodology:** CNN with Adaptive Dynamic Sine-Cosine Fitness Grey Wolf Optimizer

Dataset: BraTS 2021 (standard benchmark)

Performance: 99.98% - Highest accuracy in review

Key Innovation: Bio-inspired optimization for hyperparameter tuning

Architecture: Inception-ResNetV2

Advantages: leftmargin=*,noitemsep

- Exceptional diagnostic accuracy
- Automated hyperparameter optimization
- Reduces manual tuning effort

Limitations: Highly complex optimization process; compu- tationally expensive

Training Time: Extended due to optimization iterations

Study 24: Rajinikanth et al. (2021) - CNN-SVM Inte- gration **Methodology:** CNN-assisted segmentation + SVM classification

Dataset: Clinical MRI slices

Performance: 98% accuracy

Key Innovation: Two-stage hybrid pipeline **Advantages:** Clinically validated; proven reliability **Limitations:** Two-stage process increases inference time **Clinical Adoption:** High potential due to interpretability

B. *Category II: YOLO-Based Real-Time Detection Systems*

Object Detection Architectures (5 Studies) YOLO architectures enable single-pass object detection and classifica- tion, ideal for real-time clinical applications requiring rapid diagnosis.

Study 18: Abdusalomov et al. (2023) - Optimized YOLOv7 **Methodology:** YOLOv7 with CBAM, SPPF+, BiFPN, decoupled heads

Dataset: 10,000+ MRI images (largest in YOLO category)

Performance: 99.5% accuracy

Tumor Types: Glioma, meningioma, pituitary

Key Innovations: leftmargin=*,noitemsep

- Convolutional Block Attention Module (CBAM) for feature emphasis
- Spatial Pyramid Pooling Fast (SPPF+) for multi-scale features
- Bidirectional Feature Pyramid Network (BiFPN)

Advantages: Real-time detection with exceptional accuracy **Inference Speed:** 15-20ms per image (GPU) **Limitations:** Requires extensive training data (10,000+ images)

Study 22: Kang et al. (2025) - PK-YOLO **Methodology:**

Pretrained Knowledge Guided YOLO **Dataset:** Multiplanar MRI slices **Performance:** mAP@0.5 = 0.93

Key Innovation: Leverages pretrained knowledge for transfer learning

Advantages: leftmargin=*,noitemsep

- Multi-view analysis across axial, coronal, sagittal planes
- Effective transfer learning strategy

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- Improved generalization through pretrained weights

Limitations: Very recent (2025); limited external validation
Future Potential: High - awaiting multi-institutional testing

Study 23: Dulal & Dulal (2025) - Improved YOLOv8

Methodology: Modified YOLOv8 architecture

Dataset: Custom dataset
Performance: mAP@0.5 = 0.91

Key Innovation: Latest YOLO iteration optimizations
Advantages: Cutting-edge architecture; fast inference (10ms)

Limitations: Very recent; requires extensive validation

Deployment Readiness: Moderate - needs clinical trials

Study 25: Proposed System (2025) - YOLOv8 + VGG19

+ 3D Viz **Methodology:** Integrated YOLOv8 detection + VGG19 classification + 3D visualization

Dataset: 5,249 MRI images (glioma: 1289, meningioma: 1589, pituitary: 1560, no-tumor: 811)

Performance: mAP@0.5 = 0.92, F1-score = 0.91

Class-wise Precision: Glioma: 0.92, Meningioma: 0.89,

Pituitary: 0.94, No-tumor: 0.96

Key Innovations: leftmargin=*,noitemsep

- Web-based Flask deployment for accessibility
- Real-time processing (1.2 seconds upload-to-result)
- Interactive 3D brain visualization with Three.js
- Anatomical mapping of detected tumors
- Treatment monitoring simulation

Advantages: leftmargin=*,noitemsep

- Clinician-friendly web interface
- 3D spatial context for surgical planning
- Low false positive rate (4.2%)
- Minimal hardware requirements

Limitations: leftmargin=*,noitemsep

- Class imbalance affecting meningioma recall (0.85)
- Performance degradation on low-resolution scans (¡256x256)
- Requires further multi-institutional validation

Clinical Deployment: High potential - web-based system ready for pilot testing

Study 3: Uke et al. (2024) - IoT + OpenCV + YOLO
Methodology: Real-time video processing with YOLO
Application: Face detection and intrusion detection
Performance: 98% system reliability

Relevance: Demonstrates real-time processing capabilities

Limitations: Not medical imaging specific

Transferable Concepts: Real-time alert systems, IoT integration

A. Category III: U-Net and Segmentation Approaches

Medical Image Segmentation (3 Studies) U-Net architectures specifically designed for precise delineation of tumor boundaries, essential for surgical planning and treatment monitoring.

Study 9: Montaha et al. (2023) - 2D U-Net **Methodology:**

Automated 2D U-Net segmentation **Dataset:** BraTS2020 (standard benchmark) **Optimal Sequence:** T1-weighted MRI

Performance: Accuracy: 99.41%, DSC: 93%

Key Innovation: Cost-efficient alternative to 3D methods

Advantages: leftmargin=*,noitemsep

- Eliminates manual segmentation
- Lower computational requirements than 3D
- Excellent accuracy-efficiency tradeoff
- Suitable for resource-limited settings

Limitations: Limited to 2D slice-by-slice analysis; misses volumetric context

Processing Time: Fast - real-time capable

Study 20: Sangui et al. (2023) - Modified 3D U-Net
Methodology: Revised U-Net framework for 3D MRI
Dataset: BRATS 2020

Performance: 99.4% accuracy

Key Innovation: Handles tumor heterogeneity and tissue similarity

Advantages: leftmargin=*,noitemsep

- Full volumetric analysis
- Superior to competing deep learning frameworks
- Addresses inter-tumor heterogeneity

- Accurate healthy tissue differentiation

Limitations: Computationally expensive; requires high-end GPU

Memory Requirements: High (16GB+ GPU VRAM recommended)

Study 7: Zhu et al. (2024) - SDV-TUNet **Methodology:**

Sparse Dynamic Volume TransUNet

Dataset: BraTS2020 and BraTS2021

Key Innovation: Multi-level edge feature fusion (MEFF)

Technical Features: leftmargin=*,noitemsep

- Integrates voxel features
- Models inter-layer relationships
- Captures intra-axis characteristics
- Sparse dynamic encoder-decoder architecture

Performance: Superior to state-of-the-art **Advantages:** leftmargin=*,noitemsep

- Enhanced tumor localization
- Accurate spatial distribution mapping
- Combines global and local features

Limitations: Computationally intensive; complex architecture

Training Complexity: High - requires expertise

B. Category IV: Transformer and Hybrid Architectures

Advanced Neural Architectures (2 Studies) Integration of Transformer attention mechanisms with CNNs to capture both local features and long-range dependencies.

Study 10: Lin et al. (2023) - CKD-TransBTS **Methodology:** Clinical Knowledge-Driven Hybrid Transformer

Dataset: BraTS 2021 Challenge

Architecture: Dual-branch hybrid encoder

Key Innovation: Modality-Correlated Cross-Attention (MCCA)

Technical Approach: leftmargin=*,noitemsep

- Rearranges MRI modalities into complementary sets
- Combines Transformer and CNN strengths
- Leverages clinical domain knowledge

Performance: Surpasses current CNN and Transformer models

Advantages: leftmargin=*,noitemsep

- Captures long-range dependencies (Transformer)
- Preserves local feature extraction (CNN)
- Clinical knowledge integration

Limitations: High computational requirements

Innovation Level: High - cutting-edge architecture

Study 19: Montaha et al. (2022) - TimeDistributed-CNN-LSTM **Methodology:** Hybrid CNN-LSTM for temporal-spatial analysis

Dataset: 3D MRI sequences (all four sequences)

Performance: 98.90% accuracy

Key Innovation: Processes multiple sequences simultaneously

Temporal Analysis: Extracts temporal patterns across sequences

Advantages: leftmargin=*,noitemsep

- More effective than independent 3D CNNs
- Combines spatial and temporal information
- K-fold validation ensures robustness
- Strong potential for early diagnosis

Limitations: Complex architecture; longer training time

Clinical Value: High - assists radiologists in early detection

C. Category V: Ensemble and Multi-Modal Methods

Ensemble Learning Approaches (3 Studies) Combining multiple models or modalities to enhance robustness and accuracy through complementary predictions.

Study 8: Farhan et al. (2025) - XAI-MRI Ensemble **Methodology:** Explainable AI with dual-modality ensemble **Dataset:** BraTS dataset

Architecture: Dual U-Net ensemble with Grad-CAM **Performance:** Dice Coefficient: 97.73%, Mean IoU: 60.08%

Key Innovation: Explainability through Grad-CAM visualizations

Modality Strategy: leftmargin=*,noitemsep

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- Compares U-Net on separate modalities (T1, T2, T1ce, FLAIR)
- Merges highest-performing modalities
- Combines two best dual-modality models

Advantages: leftmargin=*,noitemsep

- Explainable predictions increase clinician confidence
- Surpasses single and dual-modality approaches
- Visualizes model decision-making pathways

Limitations: Complex ensemble architecture increases deployment complexity
Clinical Trust: High - explainability critical for adoption

Study 21: Aygu¨n et al. (2018) - Multi-Modal CNN Ensemble **Methodology:** Multi-modal CNN ensemble **Dataset:** BraTS dataset

Performance: mAP@0.5 = 0.94 (highest among ensemble methods)

Key Innovation: Leverages complementary information from different sequences

Advantages: leftmargin=*,noitemsep

- Exploits multi-modal complementarity
- Robust to single-modality failures
- High accuracy through consensus

Limitations: Requires all MRI sequences (T1, T2, T1ce, FLAIR)

Practical Constraint: Not applicable if sequences missing

Study 16: Garg & Garg (2021) - Hybrid Ensemble (KNN-RF-DT) **Methodology:** Ensemble of KNN, Random Forest, Decision Tree with Majority Voting

Dataset: 2,556 MRI images

Performance: 97.305% accuracy

Feature Extraction: Otsu's Threshold, SWT, PCA, GLCM

Classification: Benign vs. malignant

Advantages: leftmargin=*,noitemsep

- Low computational cost

  Low complexity compared to deep learning

- Interpretable decision-making
- Suitable for resource-limited settings

Limitations: Lower accuracy than pure deep learning methods

Use Case: Resource-constrained clinical environments

D. Category VI: Advanced Feature Extraction

Specialized Feature Learning (3 Studies) Novel ap- proaches to feature extraction combining wavelets, fuzzy systems, and auto-encoders.

Study 17: Abd El Kader et al. (2021) - DWAE **Methodology:** Deep Wavelet Auto-Encoder

Dataset: BRATS + ISLES (2,500 MRIs)

Performance: 99.3% accuracy

Preprocessing: Median filter, high-pass filter for denoising

Segmentation: Seed-growing method

Advantages: leftmargin=*,noitemsep

- Effective noise reduction
- Low loss during training
- Efficient feature learning through wavelets

Limitations: Limited dataset size (2,500 images) **Innovation:** Wavelet-based feature representation

Study 15: Mohan et al. (2022) - DLBTDC-MRI **Methodology:** Deep Learning with handcrafted features

Dataset: BRATS 2015

Key Techniques: leftmargin=*,noitemsep

- Adaptive fuzzy filtering for noise reduction
- Chicken swarm optimization with Tsallis entropy
- ResNet for feature fusion

Performance: High accuracy (exact percentage not specified)

Advantages: leftmargin=*,noitemsep

- Combines handcrafted and deep features
- Effective noise handling
- Bio-inspired optimization

Limitations: Requires multiple preprocessing steps

Complexity: Moderate to high

E. Category VII: 3D Visualization and AR Integration

Spatial Understanding Enhancement (4 Studies) Integra- tion of 3D visualization and augmented reality for improved spatial comprehension and surgical planning support.

Study 4: Guerroudji et al. (2024) - HoloBrain AR System **Methodology:** Low-cost mobile augmented reality **Dataset:** 496 real-patient MRI scans

Segmentation: GVF snake model **Visualization:** 3D Slicer platform **Performance:** 98.61% segmentation accuracy

Key Innovation: First low-cost mobile AR implementation

Advantages: leftmargin=*,noitemsep

- Immersive 3D visualization
- Supports surgical planning
- Mobile accessibility
- Cost-effective solution

Limitations: Requires specialized AR hardware (HoloLens or similar)

Clinical Application: Pre-operative planning, medical edu- cation

Study 6: van Doormaal et al. (2021) - Cloud-based AR Segmentation **Methodology:** Automatic segmentation for 3D AR visualization

Dataset: T1-weighted MR images

Segmentation Targets: Skin, brain, ventricles, tumors **Performance:** DSC: 0.868, Computation time: 12.5 minutes **Accuracy Pattern:** More accurate for supratentorial vs. infratentorial

Advantages: leftmargin=*,noitemsep

- Minimizes manual segmentation time
- Cloud-based processing enables thin clients
- Automatic multi-structure segmentation

Limitations: leftmargin=*,noitemsep

- Lower accuracy for infratentorial metastases
- 12.5-minute processing time

Future Enhancement: Additional MRI sequences, improved infratentorial accuracy

Study 5: Taranda & Turcan (2021) - 3D Imaging Review

Type: Comprehensive theoretical review

Focus: 3D whole-brain imaging for tumor microenvironment **Imaging Methods:** Two-photon microscopy, light-sheet flu- orescence

Key Insight: 3D spatial organization critical for tumor biology

Contribution: leftmargin=*,noitemsep

- Emphasizes volumetric distribution importance
- Reviews advanced imaging techniques
- Discusses tumor-microenvironment interactions

Limitations: Theoretical review; no direct implementation **Research Impact:** Provides foundation for 3D imaging research

F. Category VIII: Survey and Review Studies

Comprehensive Literature Analysis (4 Studies) Meta-analyses providing broad perspectives on methodologies, challenges, and future directions.

Study 11: Solanki et al. (2023) - Brain Tumor Detection Overview **Type:** Comprehensive survey

Focus: Segmentation difficulties and tumor heterogeneity **Methods Covered:** Deep learning, transfer learning, ma- chine learning

Topics: Tumor morphology, datasets, augmentation, classifi- cation

Contribution: Extensive methodology review and future directions

Value: Provides landscape overview for researchers

Study 12: Amin et al. (2022) - Machine Learning Survey

Type: Comprehensive survey

Focus: Shape, size, and location variation challenges **Methods:** ML, DL, transfer learning, quantum machine learning

Unique Aspect: Coverage of emerging quantum ML ap- proaches

Contribution: Benefits, limitations, developments, future prospects

Innovation: First to discuss quantum computing applica- tions

Study 2: Uke et al. (2024) - Object Tracking Review **Type:**

Extensive review (50+ studies, 2015-2022)

Focus: Deep learning-based object tracking

Relevance: Groundwork for real-time medical applications **Challenges Identified:** Small object visibility, real-time con- straints

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Transferable Concepts: Precise detection for improved tracking

Application: Traffic management, surveillance, medical imaging

G. Cross-Cutting Performance Analysis

1) Performance Tier Classification: **Tier 1: Exceptional Performance (¿99% Accuracy)** leftmargin=*

- Study 14 (ZainEldin): **99.98%** - Bio-inspired optimization
- Study 18 (Abdusalomov): 99.5% - Optimized YOLOv7
- Study 20 (Sangui): 99.4% - Modified 3D U-Net
- Study 9 (Montaha): 99.41% - 2D U-Net
- Study 17 (Abd El Kader): 99.3% - Deep Wavelet Auto-Encoder

Tier 2: High Performance (95-99%) leftmargin=*

- Study 19 (Montaha): 98.90% - CNN-LSTM hybrid
- Study 13 (Rahman): 98.12% - PDCNN
- Study 24 (Rajinikanth): 98% - CNN-SVM
- Study 4 (Guerroudji): 98.61% - AR segmentation
- Study 8 (Farhan

I. Research Gaps Identified

Based on the comprehensive analysis of 25 research papers, several critical research gaps have been identified that present opportunities for future investigation:

A. Dataset and Generalization Limitations

Multi-Institutional Validation Deficiency: The majority of studies rely on single-source or publicly available benchmark datasets such as BraTS, BRATS 2015-2021, and ISLES. While these standardized datasets ensure reproducibility, they limit the assessment of model generalizability across different MRI machines, imag- ing protocols, scanner manufacturers (Siemens, GE, Philips), and clinical settings. Only 3 out of 25 studies explicitly mention multi-center validation, creating a significant gap in understanding real-world performance

variability. Class Imbalance and Rare Tumor Types: Current research predominantly focuses on three major tumor categories: glioma, meningioma, and pituitary tumors. Rare tumor types such as medulloblastomas, ependymomas, oligodendrogliomas, and craniopharyngiomas receive insufficient attention. Studies report varying performance across tumor types, with meningioma consistently showing lower recall rates (0.85-0.87), indicating challenges in detecting tumors with subtle imaging characteristics or anatomical heterogeneity. Limited Longitudinal Data: No studies in the reviewed literature address tumor evolution tracking over time or treatment response monitoring using se- quential MRI scans. This represents a significant gap for applications in personalized medicine and adaptive treatment planning.

B. Computational and Deployment Challenges

Resource-Constrained Environment Implementation: While studies 18, 23, and 25 achieve impressive real- time performance (10-20ms inference) on high- end GPU hardware (RTX 3090, Tesla V100), only study 4 explicitly addresses low-cost implementation. The deployment gap between research prototypes and resource-limited clinical settings, particularly in developing countries, remains substantial. Edge computing optimization, mobile deployment strategies, and low-power hardware compatibility receive minimal atten- tion. Web and Mobile Integration: Only 2 out of 25 studies (study 25 and partially study 6) explicitly im- plement web-based interfaces for clinical deployment. The gap between achieving high laboratory performance and creating accessible, user-friendly diagnostic tools for healthcare professionals represents a critical bar- rier to adoption. Model Compression and Efficiency: While YOLOv8-based approaches demonstrate compu- tational efficiency, systematic studies on model com- pression techniques (quantization, pruning, knowledge distillation) specifically for brain tumor detection are absent. Study 9 mentions cost-efficiency compared to 3D approaches, but comprehensive efficiency-accuracy tradeoff analyses remain limited.

C. Clinical Validation and Explainability

Prospective Clinical Trials: All 25 studies report retrospective analysis on historical datasets. None present results from prospective clinical trials where models are deployed in active diagnostic workflows with radiologist validation in real-time clinical decision-making scenarios. Explainable AI Integration: Only studies 8 and 10 incorporate explainability features (Grad-CAM visualizations, attention mechanisms). The majority of high-performing models (14 achieving ¿97% accuracy) function as ”black boxes,” limiting clinical adoption where diagnostic reasoning must be transparent and verifiable by medical professionals. Regulatory Compliance: No

studies address FDA approval pathways, CE marking requirements, HIPAA compliance, or other regulatory

frameworks necessary for clinical deployment. The gap between research innovation and regulatory-compliant medical devices remains unaddressed.

D. Multi-Modal and Cross-Domain Integration

Limited Cross-Modality Fusion: While studies 8 and 21 explore multi-modal approaches combining T1, T2, T1ce, and FLAIR sequences, integration with other imaging modalities such as PET, CT, or functional MRI (fMRI) is absent. Study 5 discusses multi-modal imag- ing theoretically but lacks implementation. Clinical Data Integration: No studies integrate patient demographic data, clinical history, genetic markers, or biomarker information with imaging data for holistic diagnos- tic predictions. The potential of combining radiomics with genomics (radiogenomics) remains unexplored in the reviewed literature. Cross-Disease Generalization: All studies focus exclusively on brain tumors. Trans- fer learning potential to other neurological conditions (stroke, Alzheimer's, multiple sclerosis) or adaptation frameworks for related diagnostic tasks are not investi- gated.

E. Advanced Visualization and Spatial Understanding

Interactive 3D Visualization Limitations: Studies 4, 5, 6, and 25 incorporate 3D visualization, but comprehensive integration of interactive features, surgical trajectory planning, critical structure identification (blood vessels, eloquent cortex), and intraoperative guidance systems is limited. Augmented Reality Clinical Validation: Stud- ies 4 and 6 propose AR implementations but lack extensive clinical validation with neurosurgeons. User experience studies, workflow integration assessments, and surgical outcome evaluations are absent. Temporal 4D Visualization: No studies address 4D (3D + time) visualization for tumor growth simulation or treatment response tracking, despite study 25 mentioning this capability theoretically.

F. Methodological Gaps

Uncertainty Quantification: No studies implement Bayesian approaches, Monte Carlo dropout, or ensemble-based uncertainty estimation to provide confidence intervals for predictions—a critical feature for clinical decision support. Active Learning and Continual Learning: Research lacks exploration of active learning strategies where models can request expert annotations for uncertain cases, or continual learning frameworks where models adapt to new data distributions without catastrophic forgetting. Adversarial Robustness: No studies assess model robustness against adversarial perturbations or distribution shifts caused by different imaging protocols, which is crucial for reliable clinical deployment.

G. Ethical and Bias Considerations

Dataset Diversity and Bias: None of the 25 studies explicitly address demographic representation, ethnic diversity, or potential algorithmic bias in their train- ing datasets. Performance stratification by age, gen- der, ethnicity, or geographic origin is absent, raising concerns about equitable healthcare AI deployment. Privacy- Preserving Techniques: Despite increasing em- phasis on patient data privacy, no studies implement federated learning, differential privacy, or other privacy- preserving techniques that would enable collaborative model training without centralizing sensitive medical data.

II. FUTURE DIRECTIONS AND PROPOSED METHODOLOGY

A. Federated Learning for Multi-Institutional Collabo- ration

Proposed Approach: Implement federated learning frameworks that enable collaborative model training across multiple hospitals and research institutions with- out sharing raw patient data. This addresses privacy concerns while enabling access to diverse datasets rep- resenting different populations, imaging equipment, and clinical protocols. Technical Implementation:

- Deploy local model training at each participating institution
- Aggregate model weights using secure aggregation protocols
- Implement differential privacy mechanisms to pre- vent data leakage
- Utilize blockchain technology for transparent model versioning and contribution tracking

Expected Outcomes: Enhanced model generalizabil- ity, reduced bias, compliance with privacy regulations (GDPR, HIPAA), and facilitation of global collaboration in medical AI research.

B. Hybrid Transformer-CNN Architecture with Multi- Scale Attention

Proposed Architecture: Develop an advanced hybrid architecture combining the spatial feature extraction capabilities of CNNs with the long-range dependency modeling of Vision Transformers (ViT), incorporating

multi-scale attention mechanisms specifically designed for brain tumor characteristics.

Key Components:

- Multi-Scale CNN Encoder: Extract hierarchical features at different resolutions (1/4, 1/8, 1/16, 1/32) to capture both fine-grained tumor boundaries and global brain anatomy.

Proposed Framework: Integrate Bayesian neural networks or Monte Carlo dropout to provide uncertainty estimates alongside predictions, enabling clinicians to assess model confidence and identify cases requiring expert review.

Implementation Details:

- Implement dropout at inference time to generate multiple predictions
- Compute predictive uncertainty using variance across predictions
- Establish confidence thresholds for automatic flagging of uncertain cases
- Develop visualization tools displaying uncertainty maps overlaid on MRI images

Clinical Benefits: Reduces over-reliance on automated predictions, identifies distribution shifts, and supports human-AI collaboration in diagnostic workflows.

C. Lightweight Edge-Computing Optimized Models

Proposed Solution: Develop model compression and optimization techniques specifically tailored for deployment on resource-constrained devices including mobile phones, tablets, and low-power edge servers in rural healthcare facilities.

Optimization Techniques:

- Quantization: Convert 32-bit floating-point weights to 8-bit integers (INT8) reducing model size by 75%
- Knowledge Distillation: Train compact student models (YOLOv8-nano, MobileNetV3) mimicking larger teacher models
- Neural Architecture Search: Automatically discover optimal architectures balancing accuracy and computational efficiency
- Pruning: Remove redundant connections based on magnitude or gradient-based importance

Implementation Platform:

- TensorFlow Lite for mobile deployment (Android/iOS)
- ONNX Runtime for cross-platform compatibility
- WebAssembly for browser-based inference without server dependencies

Target Performance: ¡100MB model size, ¡50ms inference on mobile CPUs, >90% accuracy retention compared to full models.

D. Multimodal Integration Beyond MRI

Proposed System: Develop a comprehensive diagnostic platform integrating MRI with other imaging modalities, clinical data, and molecular biomarkers for holistic tumor characterization.

Data Integration Strategy:

- Imaging Fusion: Combine MRI, PET (metabolic activity), CT (bone involvement), fMRI (functional mapping)
- Clinical Embeddings: Encode patient demographics, symptoms, medical history using natural language processing
- Genomic Integration: Incorporate IDH mutation status, MGMT methylation, 1p/19q codeletion for glioma grading
- Radiomics Analysis: Extract quantitative features (texture, shape, intensity) complementing deep learning predictions

Architecture:

- Modality-specific encoders processing each data type independently
- Late fusion strategy combining features at decision level
- Attention mechanisms learning optimal weighting for different modalities
- Multi-task learning simultaneously predicting tumor type, grade, molecular subtype, and prognosis

E. Advanced 4D Visualization and Surgical Planning

Proposed Platform: Extend current 3D visualization systems (study 25) to incorporate temporal dimensions, surgical trajectory optimization, and critical structure preservation.

Key Features:

- 4D Tumor Growth Modeling: Utilize sequential MRI scans to model tumor growth trajectories and predict future expansion
- Treatment Response Simulation: Visualize expected tumor changes under different treatment protocols (radiation, chemotherapy, surgical resec-

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tion)

- Surgical Trajectory Planning: Implement optimization algorithms identifying minimal-invasiveness surgical paths avoiding eloquent cortex, blood vessels, and critical white matter tracts
- Intraoperative Guidance Integration: Real-time registration of preoperative 3D models with intraoperative imaging for navigation
- Virtual Reality Training: Develop VR modules for neurosurgical residents practicing tumor resection on patient-specific anatomies

Technical Implementation:

- Three.js/WebGL for web-based 3D rendering
- Unity3D for VR/AR applications
- Real-time mesh deformation algorithms for brain shift compensation
- Integration with neuronavigation systems (BrainLab, Medtronic StealthStation)

F. *Active Learning and Human-in-the-Loop Systems*

Proposed Framework: Implement active learning strate- gies enabling models to identify challenging cases requiring expert annotation, optimizing data labeling efficiency.

Methodology:

- Uncertainty Sampling: Prioritize samples with highest predictive uncertainty for expert review
- Query-by-Committee: Maintain ensemble of models and request annotations for disagreement cases
- Expected Model Change: Select samples that would maximally update model parameters
- Interactive Annotation Tool: Develop user-friendly interfaces for radiologists to efficiently annotate flagged cases

Continual Learning Component:

- Implement elastic weight consolidation preventing catastrophic forgetting
- Maintain memory buffer of representative samples from previous distributions
- Periodically retrain models with accumulated annotations
- Version control tracking model evolution and performance across iterations

G. *Explainable AI with Clinical Reasoning*

Proposed System: Develop comprehensive explainabil- ity frameworks generating human-interpretable justi- fications for model predictions aligned with clinical reasoning processes.

Explainability Techniques:

- Attention Visualization: Display regions of MRI images the model focuses on for predictions
    - Feature Attribution: Implement Integrated Gradi- ents, SHAP values identifying critical features
    - Counterfactual Explanations: Generate ”what-if” scenarios showing how tumor appearance changes affect predictions
    - Textual Justifications: Utilize large language mod- els generating natural language explanations of diagnostic reasoning Clinical Checklist Alignment: Map model decisions to established diagnostic criteria (WHO classifica- tion)

Validation Strategy:

- Conduct user studies with radiologists assessing explanation quality
- Measure impact of explanations on diagnostic con- fidence and decision-making
- Compare human-AI collaborative performance with AI-only or human-only baselines

- *Adversarial Robustness and Domain Adaptation*

Proposed Research: Systematically evaluate and enhance model robustness against adversarial perturba- tions and distribution shifts commonly encountered in clinical practice.

Robustness Techniques:

- Adversarial Training: Augment training with adver- sarially perturbed examples
- Domain Generalization: Implement domain-invariant feature learning across different MRI scanners
- Test-Time Adaptation: Enable models to adapt to new domains using batch normalization statistics or self-training
- Ensemble Diversity: Maintain diverse ensemble members reducing vulnerability to common failure modes

Domain Adaptation Strategy:

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- Collect data from multiple MRI scanner types (Siemens, GE, Philips) at varying field strengths (1.5T, 3T)
- Implement unsupervised domain adaptation tech- niques (DANN, CycleGAN) aligning feature dis- tributions
- Develop scanner-agnostic preprocessing pipelines normalizing intensity distributions Validate cross- domain performance systematically

- *Regulatory Pathway and Clinical Trial Design*

Proposed Framework: Establish clear pathways for tran- sitioning research prototypes into regulatory-approved medical devices through systematic clinical validation.

Regulatory Strategy:

- FDA De Novo Classification: Position system as novel diagnostic aid (Class II medical device)
- Clinical Validation Study Design: Prospective multi-center study comparing AI-assisted diagnosis vs. standard practice
- Performance Endpoints: Non-inferiority in diagnos- tic accuracy, superiority in time-to-diagnosis, inter- rater agreement improvement
- Risk Management: Comprehensive FMEA (Failure Mode and Effects Analysis) identifying potential failure scenarios

Clinical Trial Phases:

- Retrospective Validation: Extensive testing on multi-institutional archived datasets
- Observer Study: Radiologists interpreting cases with and without AI assistance
- Prospective Silent Mode: AI running parallel to clinical workflow without influencing decisions
- Prospective Active Mode: AI integrated into diag- nostic workflow with outcome tracking
- Post-Market Surveillance: Continuous monitoring of performance in real-world deployment

CONCLUSION

This comprehensive review systematically analyzed 25 research papers spanning 2015-2025, examining state- of-the-art methodologies for deep learning-based brain tumor detection, segmentation, and classification using MRI imaging. The analysis reveals significant progress in diagnostic accuracy, with modern approaches achiev- ing exceptional performance metrics: accuracies ranging from 97-99.98Key Methodological Trends: The field has witnessed a clear evolution from traditional CNN-based classification approaches (2015-2020) toward real-time object detection architectures, particularly YOLO vari- ants, which offer superior speed-accuracy tradeoffs es- sential for clinical deployment. Concurrently, U-Net and its 3D variants have established themselves as gold standards for tumor segmentation, while emerg- ing Transformer-based hybrid architectures demonstrate promise in capturing long-range spatial dependencies. Ensemble and multi-modal approaches consistently out- perform single-model systems, validating the value of leveraging complementary information from multiple MRI sequences and architectural paradigms. Perfor- mance Benchmarks: Among the reviewed studies, the highest accuracies were achieved by: ZainEldin et al. (99.98Critical Research Gaps: Despite impressive lab- oratory performance, substantial gaps exist in trans- lating research innovations to clinical practice. Multi- institutional validation remains limited, with most stud- ies relying on single-source benchmark datasets, raising concerns about generalizability across diverse clinical settings and patient populations. Computational accessi- bility represents another critical barrier—while studies report millisecond-level inference on high-end GPUs, deployment strategies for resource-constrained environ- ments receive insufficient attention. Only 2 of 25 stud- ies implemented web-based interfaces, and none con- ducted prospective clinical trials validating performance in active diagnostic workflows. Explainability features, essential for clinical trust and adoption, were incor- porated in merely 2 studies. Additionally, regulatory compliance pathways, ethical considerations regarding algorithmic bias, and privacy-preserving collaborative learning frameworks remain largely unaddressed. Future Research Directions: The review identifies ten prior- ity directions for advancing the field: (1) federated learning enabling multi-institutional collaboration while preserving privacy, (2) hybrid Transformer-CNN ar- chitectures with multi-scale attention mechanisms, (3) uncertainty-aware Bayesian frameworks providing con- fidence estimates alongside predictions, (4) lightweight edge-computing optimized models for resource-limited settings, (5) multimodal integration beyond MRI in- corporating genomic and clinical data, (6) advanced 4D visualization with surgical trajectory planning, (7) active learning and human-in-the-loop systems opti- mizing annotation efficiency, (8) comprehensive ex- plainable AI generating clinically interpretable justifica- tions, (9) adversarial robustness and domain adaptation ensuring reliable cross-institutional performance, and

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